Lecture 13 - Wave excitation force

Observation and prediction

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Wave excitation force

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Agenda

Introduction

Objectives

Introduction of different methodologies to observe and predict the wave excitation force.

[1] What does *"best performance"* mean?

Introduction

Objectives

Introduction of different methodologies to observe and predict the wave excitation force.

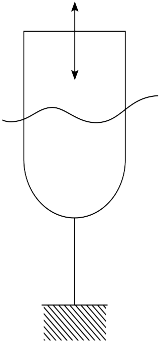
Why there is a need to obser and predict the wave excitation force?

If we want to obtain the *"best performance"* [1] out of our system we need to know both the system and the system input.
Two examples are given below

[1] What does *"best performance"* mean?

Introduction

RECAP



For a single dof, wave activated body WEC, i.e. heaving buoy or Wavestar WEC, the equation of motion can be expressed in frequency domain as: (WARNING: sign convention)

$$\left[i\omega(M + CM(\omega)) + CA(\omega) + \frac{K_{hst}}{i\omega} \right] V(\omega) = F_{ex}(\omega) + F_u(\omega) \quad (1)$$

Introducing the intrinsic mechanical impededance and substituting into the equation of motion, we obtain:

$$Z_i(\omega) = i\omega(M + CM(\omega)) + CA(\omega) + \frac{K_{hst}}{i\omega} \quad (2)$$

$$Z_i(\omega)V(\omega) = F_{ex}(\omega) + F_u(\omega) \quad (3)$$

Introduction
Optimal control

Optimal control law[2]

For a single dof wave activate body WEC, the optimal control law can be expressed in frequency domain as:

- 1 - optimal load (reactive or complex-conjugate control)

$$F_u(\omega) = -Z_i^*(\omega)V(\omega) \tag{4}$$

[2] Falnes, J. (2002). Ocean waves and oscillating systems: linear interactions including wave-energy extraction. Cambridge university press. Chapter 6.

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Optimal control

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- 1 - optimal load (reactive or complex-conjugate control)

$$F_u(\omega) = -Z_i^*(\omega)V(\omega) \tag{4}$$

- 2 - optimal velocity (phase or amplitude control)

$$V_{opt}(\omega) = \frac{F_{ex}(\omega)}{2CA(\omega)} \tag{5}$$

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Introduction

Optimal control: Requirements

- In order to control the system we need to know the excitation force.

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Optimal control: Requirements

- In order to control the system we need to know the excitation force.
- The non-causality of the excitation force requires prediction of the incoming wave.

Introduction

Optimal control: Issues

- Both the optimal velocity and the optimal load defined by the optimal control theories are often unfeasible due to the system linearity. don't try it in the lab unless the wave amplitude is very small!

[3] Korde, U. (2000). Control system applications in wave energy conversion. In OCEANS 2000 MTS/IEEE Conference and Exhibition (Vol. 3, pp. 1817-1824). IEEE.

Introduction
Optimal control: Issues

- Both the optimal velocity and the optimal load defined by the optimal control theories are often unfeasible due to the system linearity. don't try it in the lab unless the wave amplitude is very small!
- In the complex-conjugate control the prediction of the system velocity is required becasue the *irf* is anticausal [3]. The prediction of a highly damped system is often unrealiable (broad-banded response), therefore the phase control is a more roboust choice. But in this case we need to include a velocity tracking control loop.

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- The constraints are not easily implemented into the controller.

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- The constraints are not easily implemented into the controller.
- Can we still optimise the system taking care of the above issues?

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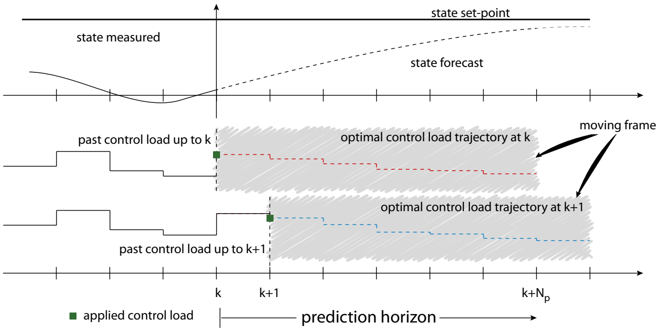
Introduction
MPC

Model	Model predictive control optimises the control trajectory,
Predictive	given a dynamic model of the system and its constraint(s)
Control	

Introduction
MPC

Model **P**redictive **C**ontrol — Model predictive control optimises the control trajectory, given a dynamic model of the system and its constraint(s)

MPC working principle



Introduction

MPC: Reference list

We will not go through the formulation details; anybody is welcome to ask question though.

- Gieske, P. (2007). Model predictive control of a wave energy converter: Archimedes wave swing. Delft University of Technology, Delft, The Netherlands.
- Cretel, J. A., Lightbody, G., Thomas, G. P., and Lewis, A. W. (2011, September). Maximisation of energy capture by a wave-energy point absorber using model predictive control. In Proceedings of the 18th IFAC World Congress, Milano, Italy, Aug (pp. 3714-3721).
- Brekken, T. K. (2011, June). On model predictive control for a point absorber wave energy converter. In PowerTech, 2011 IEEE Trondheim (pp. 1-8). IEEE.
- Hals, J., Falnes, J., and Moan, T. (2011). Constrained optimal control of a heaving buoy wave-energy converter. Journal of Offshore Mechanics and Arctic Engineering, 133(1), 011401.

Introduction

MPC: Pros and Cons

Cons (starting from the darkside):

The following points are given in comparison with a simpler PI controller

- High formulation complexity

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Introduction
MPC: Pros and Cons

Cons (starting from the darkside):

The following points are given in comparison with a simpler PI controller

- High formulation complexity
- Relative high computational cost: this can be a serius issue for non-linear MPC
- Requires to forecast the system state and the system inputs (disturbances)

Introduction
MPC: Pros and Cons

Pros:

- The constraints are embedded in the formulation of the minimisation problem.

Introduction
MPC: Pros and Cons

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- The constraints are embedded in the formulation of the minimisation problem.
- Customisable cost function

Introduction
MPC: Pros and Cons

Pros:

- The constraints are embedded in the formulation of the minimisation problem.
- Customisable cost function
- Higher performance (based on numerical simulation)

MPC
Summary

The knowledge of the excitation force is still required.
Further, the MPC requires the prediction of the excitation force over the prediction horizon.

Excitation force observers

Introduction

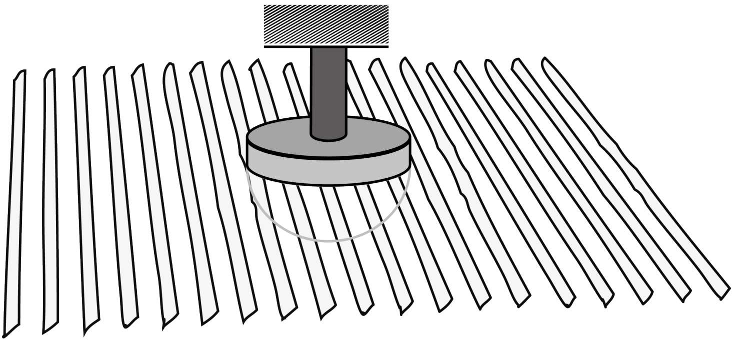
Before being able to predict the excitation force we need to measure it, but how?

Excitation force observers

Introduction

Before being able to predict the excitation force we need to measure it, but how?

Remember how the excitation force is defined



Excitation force observers

Soft sensors

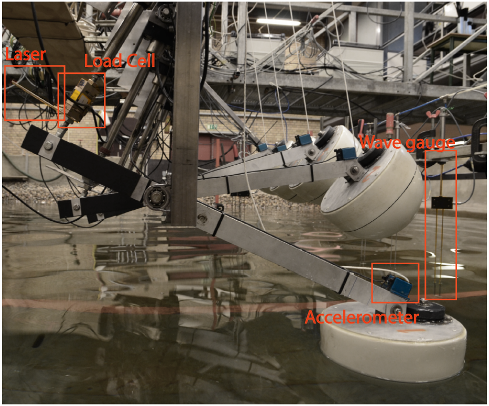
Combining measurable variables it is possible to obtain an estimation of the excitation force (observe).

Excitation force observers

Soft sensors

Which are the (commonly) measurable variables?

1 - Surface elevation
2 - System state
3 - Loads



Excitation force observers

Soft sensors

Sea surface elevation

Short term wave forecasting and excitation force observer using FIR/IIR filter [4].

- Wave prediction based on masurement up-wave (????) and wave model. FIR/IIR filters based on analytical or fitted models, i.e. wave propagation model, Auto Regressive models, Neural Networks, etc.

[4] Ferri, F., Sichani, M. T., and Frigaard, P. (2012, January). A Case Study of Short-Term Wave Forecasting Based on FIR Filter: Optimization of the Power Production for the Wavestar Device. In The Twenty-second International Offshore and Polar Engineering Conference. International Society of Offshore and Polar Engineers.

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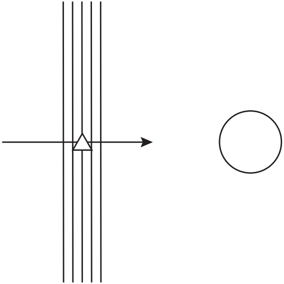

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- Convolution of the non-causal wave excitation force *irf* with the predicted sea surface at the floater location.
- The prediction of the sea surface in short crested sea states can be cumbersome!

[4] Ferri, F., Sichani, M. T., and Frigaard, P. (2012, January). A Case Study of Short-Term Wave Forecasting Based on FIR Filter: Optimization of the Power Production for the Wavestar Device. In The Twenty-second International Offshore and Polar Engineering Conference. International Society of Offshore and Polar Engineers.

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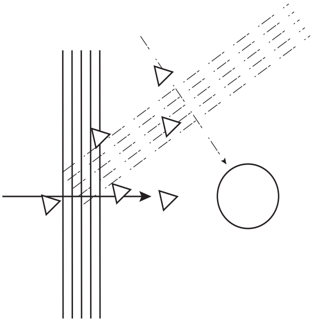

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Excitation force observers

Soft sensors

System state and applied load

Using the system state, the applied load and a model of the system is possible to assess the system input.

Excitation force observers

Soft sensors

System state and applied load

Using the system state, the applied load and a model of the system is possible to assess the system input.
Starting from the equation of motion, the excitation force can be obtained as.

$$f_{ex}[k] = f_u[k] - f_{INERTIA}(\dot{v}(t)) - f_{RAD}(v(t))[k] - f_{hst}(p(t))[k] \qquad (6)$$

here [k] represents the actual instant of time.

Excitation force observers

Soft sensors

System state and applied load

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here [k] represents the actual instant of time.
LIMITATIONS: Any error in the measurement and in the model are included in the excitation force. We miss a feedback from the system state.

Excitation force observers
Soft sensors

System state and applied load, alternatives

It is possible to use the information of the system state to evaluate the model error and then correct the excitation force assessed.

1. Luenberger observer
2. Kalman filter

Excitation force observers
Soft sensors

Luenberger observer
Given a dynamic model of a system

$$x[k+1] = Ax[k] + Bu[k] \tag{7}$$
$$y[k] = Cx[k] \tag{8}$$

Excitation force observers

Soft sensors

Luenberger observer

Given a dynamic model of a system

$$x[k+1] = Ax[k] + Bu[k] \tag{7}$$

$$y[k] = Cx[k] \tag{8}$$

If the system is observable, then it is possible to identify a matrix L such that the error between the plant (x) and the observed state ($\hat{x}$) tends to zero.

$$\hat{x}[k+1] = A\hat{x}[k] + L(y[k] - C\hat{x}[k]) + Bu[k] \tag{9}$$

$$e[k+1] = (A - LC)e[k] \tag{10}$$

The error dynamic can be chosen by varying the matrix $A - LC$

Excitation force observers

Soft sensors

Luenberger observer

How does the dynamic model of a WEC look like?

Excitation force observers

Soft sensors

Luenberger observer

How does the dynamic model of a WEC look like?
Since we want to extimate the excitation force, we need to expand the dynamic model of the system and include the excitation force.

$$A = \left[\begin{array}{cc|c|c} 0 & 1 & \underline{0} & 0 \\ -\frac{k}{J} & -\frac{d_R}{J} & -\frac{c_R}{J} & B_W \cdot C_{ex} \\ \hline \underline{0} & b_R & a_R & \underline{0} \\ \hline \underline{0} & \underline{0} & \underline{0} & A_{ex} \end{array}\right], B = \left[\begin{array}{c} 0 \\ \frac{1}{J} \\ \hline 0 \\ \hline 0 \end{array}\right], C = \left[\begin{array}{cc|c|c} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{array}\right]$$

where the state vector is defined as:

$$x[k] = \left[\begin{array}{cc|c|c} p & v & x_R & f_{ex} \end{array}\right]^T$$

Excitation force observers

Soft sensors

Luenberger observer

The excitation model is a simple integrator therefore

$$A_{ex} = 1, \quad B_{ex} = 0, \quad C_{ex} = 1$$

Other models are possible, such as oscillator observer.

Excitation force observers
Soft sensors

Luenberger observer
The excitation model is a simple integrator therefore

$$A_{ex} = 1, \quad B_{ex} = 0, \quad C_{ex} = 1$$

Other models are possible, such as oscillator observer.
The L matrix is defined as

$$L = PC^T R_L^{-1}$$

where P is obtained by solving the Riccati equation of the system

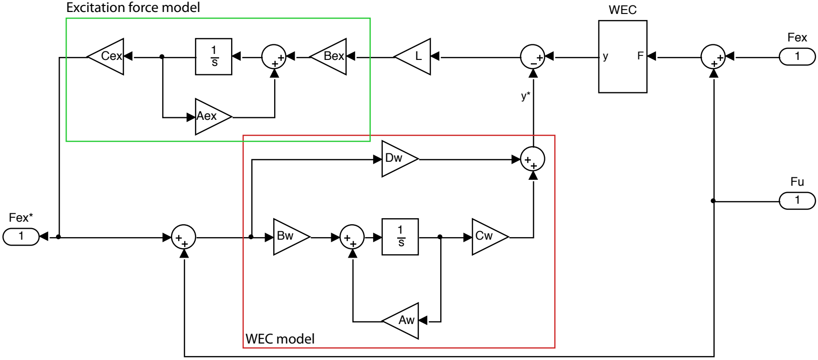
$$AP + PA^T - PC^T R_L^{-1} CP + Q_L = 0$$

Q_L and R_L are the covariance matrices of the process and the measurement (tuning parameters)

Excitation force observers

Soft sensors

Luenberger observer

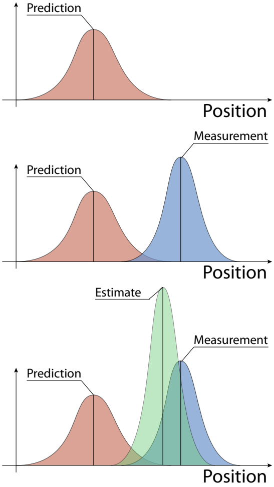


Excitation force observers

Soft sensors

Kalman filter

Kalman filter provide the best linear estimation of the system state.
It uses a statistical representation of the system and combine the system prediction with its measurements.



Excitation force observers

Soft sensors

Kalman filter

Kalman filter breakout:

- Prediction - a priori esimate
  - $\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k$
  - $P_{k|k-1} = AP_{k-1|k-1}A^T + Q_k$

Excitation force observers
Soft sensors

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Kalman filter breakout:

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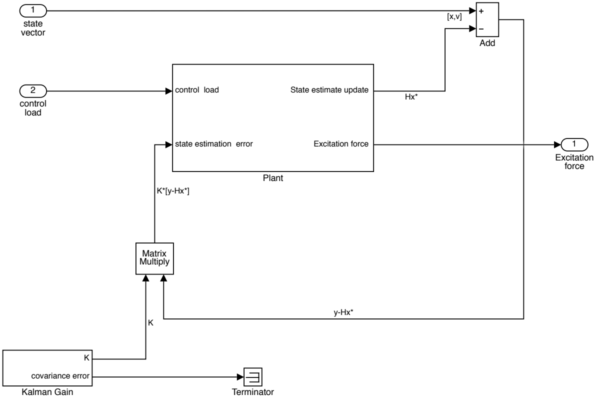
  - $P_{k|k-1} = AP_{k-1|k-1}A^T + Q_k$
- Update - a posteriori estimate
  - $\tilde{y}_k = y_k - C\hat{x}_{k|k-1}$
  - $S_k = CP_{k|k-1}C^T + R_k$
  - $K_k = P_{k|k-1}C^T S_k^{-1}$
  - $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\tilde{y}_k$
  - $P_{k|k} = (I - K_k C)P_{k|k-1}$

Excitation force observers

Soft sensors

Kalman filter



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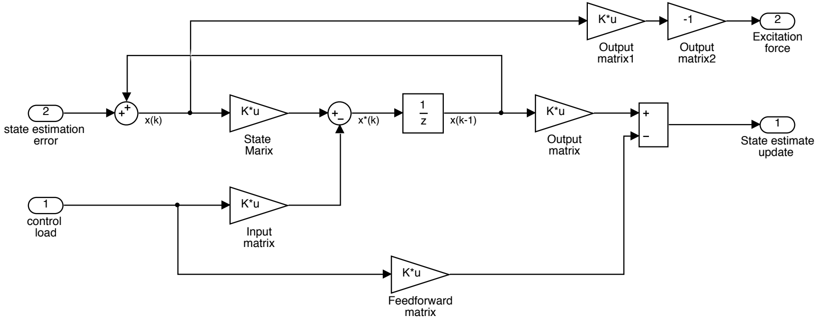
Kalman filter



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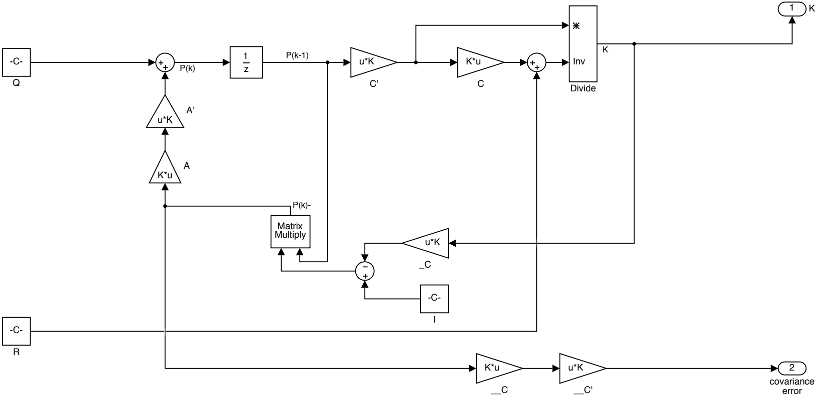

Excitation force prediction
Introduction

Once the excitation force is known it is possible to predict its evolution in time. Excitation force models:

- Autoregressive Model
- Cyclical Model
- Cyclical Model with variable frequency

Alternatives

Nerural network and Fuzzy Logic are also viable solutions

Excitation force prediction
Autoregressive Model

Autoregressive (AR) model assumptions:
the variable can be predicted using a linear combination of the past value of the variable

$$\hat{f}_{ex}[k+1|k] = \sum_{i=0}^{N-1} a_i \cdot f_{ex}[k-i]$$

Excitation force prediction

Cyclical Model

Cyclical model assumptions:
the excitation force is expressed as a superposition of a number *m* of linear harmonic components. The choice of *m* and the distribution of the harmonics within the wave spectrum is a key point.

Excitation force prediction

Cyclical Model

Cyclical model assumptions:
the excitation force is expressed as a superposition of a number *m* of linear harmonic components. The choice of *m* and the distribution of the harmonics within the wave spectrum is a key point.
Assuming the index *i* ranging from 1 to *m* the model can be expressed as:

$$\begin{bmatrix} \psi_i[k+1] \\ \psi_i^*[k+1] \end{bmatrix} = \begin{bmatrix} cos(w_i \Delta T) & sin(w_i \Delta T) \\ -sin(w_i \Delta T) & cos(w_i \Delta T) \end{bmatrix} \begin{bmatrix} \psi_i[k] \\ \psi_i^*[k] \end{bmatrix} + \begin{bmatrix} \xi_i[k] \\ \xi_i^*[k] \end{bmatrix} \quad (11)$$

$$f_{ex}[k] = \sum_{i=1}^{m} \psi_i[k] + \zeta[k] \quad (12)$$

Excitation force prediction

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$$f_{ex}[k] = \sum_{i=1}^{m} \psi_i[k] + \zeta[k] \quad (12)$$

The best estimation of $\hat{f}_{ex}[k|k]$ is obtained usign a Kalman filter, while the N-step ahead prediction is achieved from the free-evolution of the dynamical model ($\hat{f}_{ex}[k+N|k] = CA^N \hat{x}[k|k]$).

Excitation force prediction

Cyclical Model with variable frequency

Cyclical model with variable frequency assumptions:
the excitation force is expressed as a superposition an harmonic components, which frequency is a function of time. This eliminate the error in the placement of the harmonic components but generate a non-linear system.

Excitation force prediction

Cyclical Model with variable frequency

Cyclical model with variable frequency assumptions:
the excitation force is expressed as a superposition an harmonic components, which frequency is a function of time. This eliminate the error in the placement of the harmonic components but generate a non-linear system.
The excitation force is now defined by a single cyclical model as:

$$\begin{bmatrix} \psi_i[k+1] \\ \psi_i^*[k+1] \\ \omega[k+1] \end{bmatrix} = \begin{bmatrix} cos(\omega[k]\Delta T) & sin(\omega[k]\Delta T) & 0 \\ -sin(\omega[k]\Delta T) & cos(\omega[k]\Delta T) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \psi_i[k] \\ \psi_i^*[k] \\ \omega[k] \end{bmatrix} + \begin{bmatrix} \xi_i[k] \\ \xi_i^*[k] \\ \kappa[k] \end{bmatrix} \tag{13}$$

$$f_{ex}[k] = \psi_i[k] + \zeta[k] \tag{14}$$

Excitation force prediction

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$$f_{ex}[k] = \psi_i[k] + \zeta[k] \tag{14}$$

Since the model is non-linear an Extended-Kalman filter can be used to obtain the excitation force estimation.

Excitation force prediction
Side notes

Search for Fusco F, for a number of publications over this matter.

TIP: The prediction methods proposed have a GOF below 50%. In order to increase the number it is possible to low pass filter the signal. Indeed we are interested mostly in the prediction of the low frequency component of the spectrum.

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